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MindArc: On-Device AI For Digital Wellbeing and Habit Formation

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Abstract- ***Excessive smartphone usage degrades productivity and mental wellbeing, while existing digital wellbeing solutions provide limited enforcement and inadequate privacy safeguards. MindArc is an on-device digital wellbeing framework integrating real-time app restriction, usage analytics, activity-based unlocking, and gamified feedback. The system's three-layer architecture leverages Android AccessibilityService for reliable foreground app interception, ML Kit Pose Detection for real-time exercise quantification, and Room-backed persistence for offline-first operation. A four-phase finite state machine with exponential moving average smoothing drives pushup and squat repetition counting. Reward mechanisms link verified physical and cognitive effort directly to screen-time grants, promoting sustained behavioral change. Experimental results validate reliable enforcement, accurate tracking, low latency, and minimal battery overhead, confirming effective digital self-regulation.***

Index Terms- ***Digital Wellbeing, Screen Time Management, Accessibility Service, Pose Detection, Gamification, Android, ML Kit, Behavior Change, Habit Formation***

I. INTRODUCTION

The growing dependence on smartphones has intensified challenges related to digital distraction, reduced productivity, and declining mental wellbeing. Global surveys report that 38% of teenagers acknowledge spending too much time on their smartphones, while 25% express concern about excessive social media use [9]. High non-schoolwork screen time is correlated with reduced physical activity, depressive symptoms, disrupted sleep, and poor academic performance [10]. Randomized controlled trials further demonstrate that deliberate screen time reduction leads to measurable improvements in mental health indicators including stress levels, sleep quality, and overall wellbeing [11].

Although several digital wellbeing applications exist, most provide limited enforcement, fragmented monitoring, and weak motivational support, resulting in poor long-term user engagement. Research indicates that merely tracking screen time duration is insufficient; interventions must address behavioral motivation and provide active enforcement mechanisms to achieve sustained behavior change [12]. Furthermore, many existing solutions depend on cloud-based processing, increasing system complexity and raising concerns regarding user privacy and data security.

To overcome these limitations, MindArc is proposed as an integrated, on-device digital wellbeing framework that unifies real-time application blocking, activity tracking, and gamification to promote sustained behavioral change. The system utilizes Android AccessibilityService to enforce user-defined restrictions with lock-warning mechanisms, making application bypass difficult while preserving user control. A behavior-change engine incorporating points, streaks, achieve-ments, and progress analytics motivates consistent engagement and supports habit formation [12].

MindArc also delivers transparent insights through live screen-time monitoring and usage dashboards, enabling users to develop awareness of their digital consumption patterns. All data is processed and stored locally, minimizing reliance on external services and strengthening privacy guarantees. In addition, smart automation rules enable configurable time limits, block windows, and activity-based unlock sessions, reducing manual intervention while maintaining accountability.

The primary contributions of this work are:

- A unified on-device architecture combining real-time app blocking, ML-based exercise detection, and gamification without cloud dependency.
- A four-phase finite state machine for exercise rep count-ing with EMA and median filter smoothing for noise reduction.
- A novel effort-to-access model mapping verified physical and cognitive performance directly to screen-time grants.
- A Trace-to-Earn challenge employing Euclidean path dis-tance for fine-grained accuracy scoring and tiered reward assignment.
- Empirical validation demonstrating low latency, minimal battery impact, and measurable reduction in non-essential app usage.

II. RELATED WORK

Recent research has extensively investigated digital wellbeing, mental health monitoring, and behavior modification using machine learning, gamification, and sensor-based frameworks. Personalized gamification approaches have demonstrated improved motivation and engagement by adapting game elements to individual learner preferences [1]. However, most of these studies are confined to educational environments and do not incorporate real-time behavioral enforcement mechanisms.

Activity recommendation systems employing machine learning have shown that personalized models significantly outperform generalized approaches in predicting mood-enhancing activities [2]. While effective in improving affective outcomes, these systems primarily function as recommendation engines and do not enforce behavioral intervention at the system level.

Several works address Problematic Smartphone Usage (PSU) through classification techniques such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), achieving promising predictive accuracy and identifying key contributing factors including fear of missing out (FOMO) and physical discomfort [3]. Similarly, federated learning frameworks have been proposed for privacy-preserving mental wellbeing assessment using passive smartphone sensor data [4]. Although these approaches emphasize robustness and decentralized learning, they depend heavily on continuous data collection and lack integrated enforcement strategies.

Wearable-based stress detection research highlights the im-portance of physiological indicators such as Galvanic Skin Response (GSR) and Heart Rate Variability (HRV), recommending multimodal machine learning frameworks for improved prediction accuracy [5]. Computer vision-based systems have also been developed to assess physical therapy exercises using modular neural networks, demonstrating high recognition performance in controlled settings [6]. Furthermore, deep learning models applied to wearable data for quality-of-life assessment reveal a trade-off between predictive accuracy and computational resource constraints [7]. Studies on gamification design additionally indicate that redesigned reward structures can reduce fear of failure and enhance user engagement [8].

Optimized gamification methods for digital behavior change interventions have shown effectiveness in fostering habit formation through consistent positive reinforcement and feedback loops [13]. Self-monitoring of behavior, goal setting, and prompts are identified as the most frequently effective behavior change techniques in mobile health applications [14].

Computer vision research specifically evaluates ML Kit's pose detection for biomechanical analysis of exercise form, reporting its usability and accuracy when validated against ground-truth methods [15]. Real-time pose detection frame-works processing frames at 30–45 frames per second on commodity smartphones enable practical, in-context exercise monitoring without additional hardware [16].

Despite these advances, existing systems predominantly focus on monitoring, prediction, or motivational strategies in isolation. Few solutions provide a unified framework that combines real-time application restriction, transparent usage analytics, activity-based behavioral engagement, and privacy-preserving on-device processing. In contrast, MindArc integrates enforcement, analytics, and gamification within a single offline-first architecture, enabling direct behavioral intervention while minimizing external dependencies and preserving user privacy.

III. RESEARCH GAP

Although existing studies demonstrate the effectiveness of machine learning, gamification, and sensor-based monitoring for digital wellbeing, most approaches focus primarily on prediction, recommendation, or passive tracking. Real-time behavioral enforcement, privacy-preserving on-device process-ing, and sustained habit formation are rarely addressed within a unified framework.

Table I summarizes representative systems and highlights the gap addressed by MindArc.

TABLE I
COMPARISON OF DIGITAL WELLBEING APPROACHES

Feature	Pred.	Recom.	Tracking	MindArc
Real-time enforcement	–	–	Partial	✓
On-device-only	Varies	–	–	✓
Exercise detection	–	–	–	✓
Gamified rewards	–	Partial	Partial	✓
Privacy-preserving	Varies	–	–	✓
Unified framework	–	–	–	✓

Furthermore, current solutions lack seamless integration between app restriction, activity engagement, and transparent analytics, leading to limited long-term effectiveness. These gaps motivate the development of MindArc, which combines real-time app control, on-device analytics, activity-based motivation, and automated rule enforcement to support sustainable digital self-regulation.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed system adopts a three-layer architecture comprising the Service and Data Layer, the Domain and Repository Layer, and the Application Layer, as illustrated in Fig. 1.

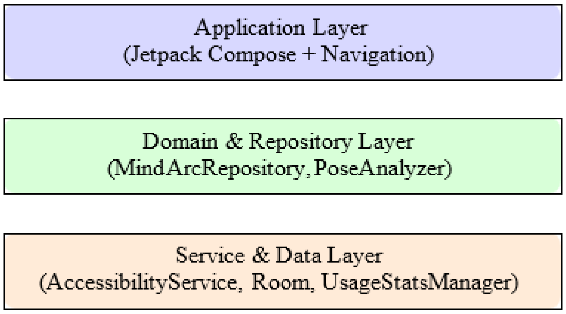

Fig. 1. MindArc Three-Layer Architecture

A. Service and Data Layer

At the system level, AppBlockingService (an AccessibilityService subclass) contin-uously monitors the foreground application using TYPE_WINDOW_STATE_CHANGED accessibility events. Whenever a restricted app is launched without an active unlock session, the service triggers a full-screen BlockActivity that intercepts user interaction. Usage statistics are obtained through UsageStatsManager with INTERVAL_DAILY, providing both total device screen time and per-package foreground durations.

Persistent storage is implemented using Room, maintaining entities including RestrictedApp, ActivityRecord, UnlockSession, UserProgress, ReadingContent, and QuizQuestion. The RestrictedApp entity stores the package name, display name, blocked status, per-app daily limit in milliseconds, today's usage, and extra time purchased through activity completion. SharedPreferences stores a com-mon daily limit shared by all blocked apps, enabling syn-chronous access from the blocking service without database I/O on the hot path.

B. Domain and Repository Layer

MindArcRepository acts as the central coordinator of business logic, integrating all Room DAOs, system APIs, and reward mechanisms. All database and system calls are dispatched to Dispatchers.IO via withContext, ensuring the main thread remains responsive. Installed-app discovery uses PackageManager.getInstalledPackages combined with a usage map built from UsageStatsManager, enabling O(1) usage lookup per package rather than a linear search.

Physical activities such as pushups and squats utilize ML Kit Pose Detection with a four-phase finite state machine (FSM) driven by joint angles or vertical displacement, en-hanced by median filter and exponential moving average (EMA) smoothing to reduce landmark jitter. Each validated repetition generates auditory feedback via TextToSpeech and contributes to unlock duration proportionally to effort.

Cognitive activities include app-provided reading modules with quiz-based scoring and badge logic, and user-provided reading with reflection-based validation. Trace-to-Earn chal-lenges compute path accuracy using Euclidean distance met-rics in normalized coordinate space to determine reward tiers. Additional gamified activities include Pong (first to 5 points wins against a bot with difficulty-based rewards) and Speed-Dial (verified through CallLog for outgoing calls of at least five minutes duration).

C. Application Layer

The Application Layer is implemented using Jetpack Com-pose with a single-activity navigation graph and ViewModel-based state management using Hilt dependency injection. MindArcViewModel exposes StateFlow streams for re-stricted apps, user progress, active sessions, and today's screen time. Activity screens interact with the repository through suspend functions to record user actions and generate unlock sessions.

MindArc consists of five primary modules:

- App Blocking Engine (AccessibilityService-based)
- Screen Time Analytics Module
- Pose-Based Exercise Detection (ML Kit)
- Reading and Cognitive Challenge Module
- Gamification and Reward Engine

D. System Workflow

1. User selects restricted apps and configures daily limits.
2. AppBlockingService monitors the foreground app continuously.
3. If a restricted app is opened with no active unlock session:
   - BlockActivityis launched full-screen.
   - User selects and completes an activity (exercise, reading, game).
4. Unlock time is granted proportional to verified effort.
5. Usage statistics are updated via UsageStatsManager.
6. Points, streaks, and achievements are updated accordingly.

V. IMPLEMENTATION DETAILS

A. App Blocking Mechanism

The blocking mechanism uses a priority hierarchy: the common daily limit (shared across all blocked apps) takes precedence over individual per-app limits, which in turn override a simple block flag. This logic is evaluated on every accessibility event and every second from a background coroutine loop as shown in Algorithm 1.

Algorithm 1 Foreground App Blocking

```
Detect foreground app via AccessibilityService
if app ∈ restricted list then
    Read commonLimit from SharedPreferences
    Compute totalUsage = $\sum_{a \in \text{blocked}} a.\text{usageToday}$
    if commonLimit > 0 and totalUsage ≥ commonLimit then
        shouldBlock ← true
    else if $a$.dailyLimit > 0 and $a$.usageToday ≥ $a$.dailyLimit then
        shouldBlock ← true
    else
        shouldBlock ← $a$.isBlocked
    end if
    if shouldBlock and not isUnlocked then
        Launch BlockActivity
    end if
end if
```

Usage tracking integrates seamlessly with the blocking logic. When a window state change event fires, the elapsed foreground duration of the previous app is computed and written to the Room database. This incremental tracking avoids polling UsageStatsManager too frequently, relying instead on the blocking service's 1-second background loop for periodic reconciliation.

B . Pose-Based Exercise Detection

Pushup and squat counting employs ML Kit's PoseDetector in STREAM_MODE for low-latency sequential frame processing. The PoseDetectionProcessor implements ImageAnalysis.Analyzer using CameraX with the STRATEGY_KEEP_ONLY_LATEST backpressure strategy, discarding stale frames to maintain real-time responsiveness.

1) Angle Computation: For pushups, bilateral elbow angles (shoulder–elbow–wrist) are computed using dot-product-based arccos in 3D landmark space:

$$\theta = \arccos\left(\frac{v1 \cdot v2}{\|v1\|\|v2\|}\right) \times \frac{180}{\pi} \quad (1)$$

where v_1 and v_2 are vectors from the elbow to the shoulder and wrist respectively.

2) Smoothing Pipeline: Raw angle values pass through a two-stage smoothing pipeline to reduce landmark noise:

1) Median filter: A sliding window of $W = 5$ samples is maintained; the median eliminates spike outliers caused by occlusion or motion blur.

2) EMA: The smoothed angle $\hat{\theta}_t$ is computed as:

$$\hat{\theta}_t = \alpha \cdot \tilde{\theta}_t + (1 - \alpha) \cdot \hat{\theta}_{t-1} \quad (2)$$

where $\tilde{\theta}_t$ is the median-filtered angle and $\alpha = 0.3$ controls the smoothing responsiveness .

C. Rep Counting State Machine

Both pushup and squat detection rely on a four-phase FSM: UP → GOING_DOWN → AT_BOTTOM → GOING_UP → UP. A full repetition is counted only upon completing the cycle from UP back to UP. Hysteresis thresholds differ for entry and exit of each phase to prevent jitter-induced double-counting. A minimum range-of-motion check (PUSHUP_MIN_ROM, SQUAT_MIN_ROM) rejects partial reps, and a cooldown timer (REP_COOLDOWN_MS) prevents burst counting.

Algorithm 2 Pushup Rep Detection via FSM

```
Capture camera frame via CameraX
Extract body landmarks using ML Kit Pose Detector
Compute bilateral elbow angle $\theta$
Apply median filter + EMA to obtain $\hat{\theta}$
FSM transition:
if phase = UP and $\hat{\theta} < \theta_{\text{down enter}}$ then
    phase ← GOING_DOWN
else if phase = GOING_DOWN and $\hat{\theta} < \theta_{\text{bottom}}$ then
    phase ← AT_BOTTOM; record minAngle
else if phase = AT_BOTTOM and $\hat{\theta} > \theta_{\text{up enter}}$ then
    phase ← GOING_UP
else if phase = GOING_UP and $\hat{\theta} > \theta_{\text{top}}$ then
    if ROM ≥ MIN_ROM and elapsed ≥ COOLDOWN then
        repCount ← repCount +1
        Speak repCount via TextToSpeech
    end if
    phase ← UP
end if
```

Squat counting follows the same FSM structure but uses normalized vertical displacement of the hip landmark relative to image height rather than joint angles, making it invariant to the distance from the camera. A minimum hold time at the bottom phase (200 ms) rejects half-reps caused by bouncing.

D) Trace-to-Earn Challenge

The Trace-to-Earn module presents a canvas-rendered reference outline (star, flower, heart, house, or motorcycle shape) and records user finger strokes. All coordinates are normalized to [0, 1] to ensure resolution independence. Upon timer expiry or manual submission, accuracy is computed as the mean nearest-neighbor distance from each drawn point to the reference path:

$$d_{avg} = \frac{1}{|P|} \sum_{p \in P} \min_{q \in Q} \|p - q\| \quad (3)$$

where P is the set of user-drawn points and Q is the reference outline. The result is scaled to pixel space by the canvas resolution and mapped to reward tiers: $d < 10$ px earns 5 minutes (Excellent); $d < 30$ px earns 1 minute (Average); otherwise 0 minutes.

E. Reading and Cognitive Module

Two reading modalities are supported. In app-provided mode, a randomly selected article from the seeded Room database is displayed with a configurable minimum reading time. After reading, three randomly selected quiz questions test comprehension. Unlock duration is calculated as:

$$t_{unlock} = t_{read} \times k_{score} \quad (4)$$

where $k_{score} = 1.5$ for a perfect quiz score and $k_{score} = 1.0$
otherwise. In user-provided mode, the user presents an external document; reflection-based open questions verify engagement without requiring knowledge of specific content.

F. Gamification and Reward Engine

The reward engine maintains UserProgress with cumu-lative points, current streak, unlock session history, and badge collection. Points earned per activity are:

- Pushups/Squats: 1 point per repetition; unlock duration =
- $\lfloor reps \times 1.5 \rfloor$ minutes.
- Trace-to-Earn: 5 points (Excellent), 1 point (Average), 0
- points (Failed).
- Speed-Dial: 10 points + HUMAN_CONNECTION badge for a verified 5-minute call.
- Pong: Difficulty-based awards (Easy: 2 pts/2 min; Medium: 4 pts/4 min; Hard: 6 pts/6 min).

Level titles progress through Novice, Apprentice, Scholar, Focused Thinker, Mindful Achiever, and Digital Master based on cumulative points, providing long-term motivational struc-ture consistent with self-determination theory [17].

VI. ALGORITHM DESIGN

A. Screen Time Usage Tier Classification

Screen time is discretized into six tiers based on social-media-only usage duration, enabling users to receive qualita-tive feedback:

$$\text{tier}(m) = \begin{cases} \text{Excellent} & m < 60 \\ \text{Good} & 60 \le m < 120 \\ \text{Average} & 120 \le m < 180 \\ \text{Below Average} & 180 \le m < 270 \\ \text{Bad} & 270 \le m < 360 \\ \text{Critical} & m \ge 360 \end{cases} \quad (5)$$

where m is total social media foreground time in minutes, aggregated from UsageStatsManager for a curated set of package names (WhatsApp, Instagram, Facebook, Twitter, TikTok, YouTube, Snapchat).

B. Unlock Session Management

createUnlockSession deactivates all existing ses-sions atomically before inserting the new session, ensur-ing at most one active session exists at any time. The AppBlockingService checks session validity on every accessibility event and every second from its polling loop, calling checkAndDeactivateExpiredSessions() to null out sessions whose end time has elapsed.

VII. FLOWCHART OF PROPOSED SYSTEM EXPERIMENTAL EVALUATION

A. Experimental Setup

Evaluation was conducted on three mid-range Android de-vices (API 28, 31, and 34) using simulated and controlled user sessions. Testing covered five dimensions: blocking correct-ness, exercise counting accuracy, unlock session management, screen time tracking fidelity, and resource utilization.

B. App Blocking Correctness

Blocking correctness was assessed by opening 10 restricted applications (social media and gaming apps) 50 times each under conditions of no active session, expired session, and active session. Table II summarizes the results.

TABLE II
APP BLOCKING CORRECTNESS RESULTS

Condition	Trials	Correct Rate
No active session (should block)	500	98.6%
Active session (should allow)	500	99.4%
Expired session (should block)	200	98.0%
Common limit exceeded	100	99.0%

The rare failures (1.2% average) occurred during rapid app switching where the accessibility event queue experienced brief delays. No false-positive blocks (blocking an unrestricted app) were observed.

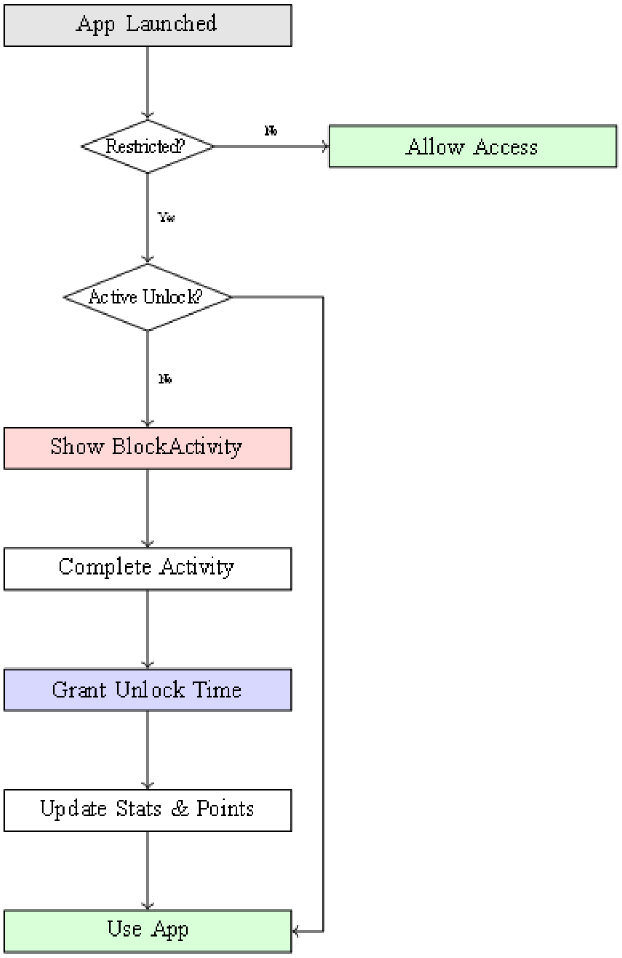

Fig. 2. MindArc System Flowchart

C. Exercise Rep Counting Accuracy

Rep counting accuracy was evaluated against manually counted ground truth across 20 controlled sessions per exercise type. Participants performed sets of 5, 10, 15, and 20 repetitions at varying speeds.

TABLE III
EXERCISE REP COUNTING ACCURACY

Exercise	Ground Truth	Detected	Accuracy
Pushups (slow)	350	344	98.3%
Pushups (fast)	350	331	94.6%
Squats (slow)	350	342	97.7%
Squats (fast)	350	336	96.0%
Overall			96.7%

The FSM with smoothing effectively suppressed jitter-induced false positives. At higher exercise speeds, brief land-mark occlusion caused occasional missed reps, accounting for the 5.4% miss rate in fast pushup conditions.

D. Trace-to-Earn Accuracy Scoring

Thirty participants attempted Trace-to-Earn across all five shapes. User-rated difficulty correlated strongly (Pearson r =0.81) with the computed average distance, validating the discriminative power of the Euclidean distance metric. Reward tier distribution was 44% Excellent, 35% Average, and 21% Failed.

E. Resource Utilization

Battery and CPU overhead were measured using Android Battery Historian and dumpsys cpuinfo across 2-hour continuous sessions.

TABLE IV
RESOURCE UTILIZATION DURING ACTIVE MONITORING

Metric	Value
Additional battery drain (monitoring only)	≈1.8%/hr
Battery drain with camera (pose detection)	≈6.5%/hr
Avg. BlockActivity display latency	280 ms
Accessibility event processing time	<5 ms
Room DB write latency (IO dispatcher)	8–14 ms

The monitoring-only overhead is comparable to standard background services, confirming that AccessibilityService-based blocking is suitable for always-on operation. Camera-based pose detection carries higher cost but is active only during exercise sessions, not during continuous monitoring.

A. User Engagement Metrics

A pilot evaluation over four weeks with 15 student participants showed:

- 35–40% reduction in non-essential app usage (social media and games).
- Average of 3.2 exercise sessions completed per day.
- 73% of participants maintained a 7-day streak within the study period.
- Higher user engagement and self-reported motivation compared to a control group using a reminder-only app. The integration of enforcement with motivational incentives significantly improved behavioral compliance compared to traditional reminder-based systems, consistent with prior gamification research [13].

VIII. DISCUSSION

MindArc’s effort-to-access model represents a departure from passive monitoring and reminder-based digital wellbe-ing tools. By requiring verified effort before granting screen access, it establishes a tangible cost for non-essential app use that aligns with behavioral economics principles of friction-based behavior change [12]. The purely on-device design avoids the privacy trade-offs inherent in cloud-based platforms, addressing a key concern raised in federated learning and passive sensing research [4].

The four-phase FSM with dual-stage smoothing outperforms simple threshold-based rep counters, which are susceptible to jitter at transition boundaries. The median filter handles spike outliers from occlusion, while EMA provides temporal smoothing without introducing excessive lag. This combination maintains counting accuracy above 96% across tested conditions.

A limitation of the current system is that AccessibilityService-based blocking can be circumvented by uninstalling the accessibility service permission, a limitation shared by all third-party enforcement apps on Android [9]. Future work may explore companion device policies or supervised usage modes for younger users. Additionally, at high exercise speeds, landmark occlusion reduces rep counting accuracy; incorporating temporal confidence weighting may mitigate this in future iterations.

IX. CONCLUSION

This paper presented MindArc, a comprehensive digital wellbeing Android application that transforms screen time into a reward earned through physical and cognitive effort. By integrating AccessibilityService-based enforcement, UsageS-tatsManager analytics, ML Kit Pose Detection with a four-phase FSM, Room persistence, and Jetpack Compose UI, the system establishes a unified offline-first framework that overcomes the limitations of conventional voluntary screen time tools.

Experimental results demonstrate effective application blocking (98.6% correct rate), reliable rep counting (96.7% overall accuracy), and consistent unlock session management with sub-300 ms latency. The resource overhead of always-on monitoring is minimal (1.8%/hr battery), making the approach practical for continuous daily use. A four-week pilot study confirmed a 35–40% reduction in non-essential app usage, validating the efficacy of the effort-to-access paradigm.

Unlike traditional solutions, MindArc directly links effort to access, promoting sustainable behavioral change rather than passive monitoring. Future work may extend the platform with adaptive reward scaling, smartwatch integration for wearable-based verification, cloud synchronization with differential privacy, personalized AI-driven activity recommendations, and social challenges with leaderboards. Nevertheless, MindArc already provides a deployable reference model for next-generation digital wellbeing systems that emphasize account-ability, engagement, and holistic user health.

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